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[54] **HIERARCHICAL PATTERN RECOGNITION SYSTEM WITH VARIABLE SELECTION WEIGHTS**

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Related U.S. Application Data

[63] Continuation-in-part of Ser. No. 464,247, Jan. 12, 1990, abandoned.

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[52] U.S. Cl. 382/15; 382/10; 395/23; 395/24
[58] Field of Search 382/14, 15, 37, 38, 382/10, 1; 364/513; 395/21, 23, 24

[56] **References Cited**

U.S. PATENT DOCUMENTS

4,914,704 4/1990 Carpenter et al. 382/14

FOREIGN PATENT DOCUMENTS

WO88/10476 12/1988 European Pat. Off. G06K 9/66

OTHER PUBLICATIONS

Cohen et a.,, "Speech Perception and Production By A Self-Organizing Neural Network," In *In Evolution, Learning. Cognition and Advanced Architecture*, Y. C. Lee (Ed), Hong Kong: World Scientific Publishers, 1988.
Carpenter et al., "Search mechanisms for Adaptive Resonance Theory (ART) Architectures," IJCNN International Joint Conference on Neural Networks,

Sheraton Washington Hotel, Jun. 19-22, 1989, pp. 201-205 (see whole document).
B. Kosko, "Competitive Adaptive Bidirectional Associative Memories," IEEE First International Conference on Neural Networks, San Diego, Calif., Jun. 21-24, 1987, pp. II-759-II-766.
Carpenter et al., "ART 3: Hierarchical Search Using Chemical Transmitters in Self-Organizing pattern Recognition Architectures", Neural Networks, vol. 3, No. 2, 1990, pp. 129-152.
G. A. Carpenter & S. Grossberg, "ART 2: Self-Organization of Stable Category Recognition Codes for Analog Input Patterns" *Applied Optics*, Dec. 1, 1987, pp. 4919-4930.
G. A. Carpenter 7 S. Grossberg, "The ART of Adaptive Pattern Recognition by a Self-Organizing Neural Network", IEEE, *Computer*, vol. 21, No. 3, pp. 77-88, Mar. 1988.

Primary Examiner—David K. Moore
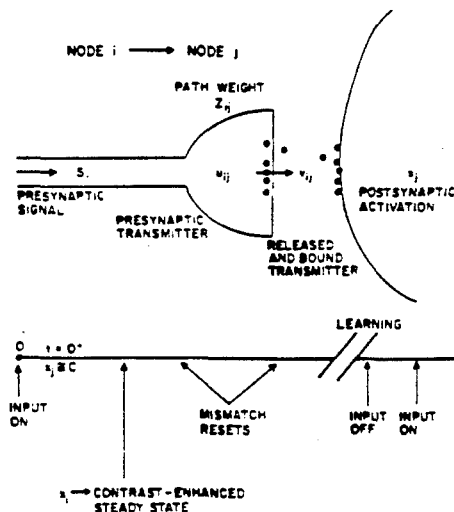*Assistant Examiner*—Michael Cammarata
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[57] **ABSTRACT**

In a pattern recognition system, input signals are applied to a short term feature representation field of nodes. A pattern from the short term feature representation field selects at least one category node in a category representation field. The selected category then generates a template pattern. With an insufficient match between the input pattern and template pattern, the category selection is reset. Category selection is based on selection weights which are initially set equal to long term memory weights. After reset, however, selections weights are reduced. Reduction is greatest at those nodes where excitation in F_2 was greater prior to reset. The category representation field is of the same form as the field which receives the input and may itself serve as an input to a higher level pattern recognition system.
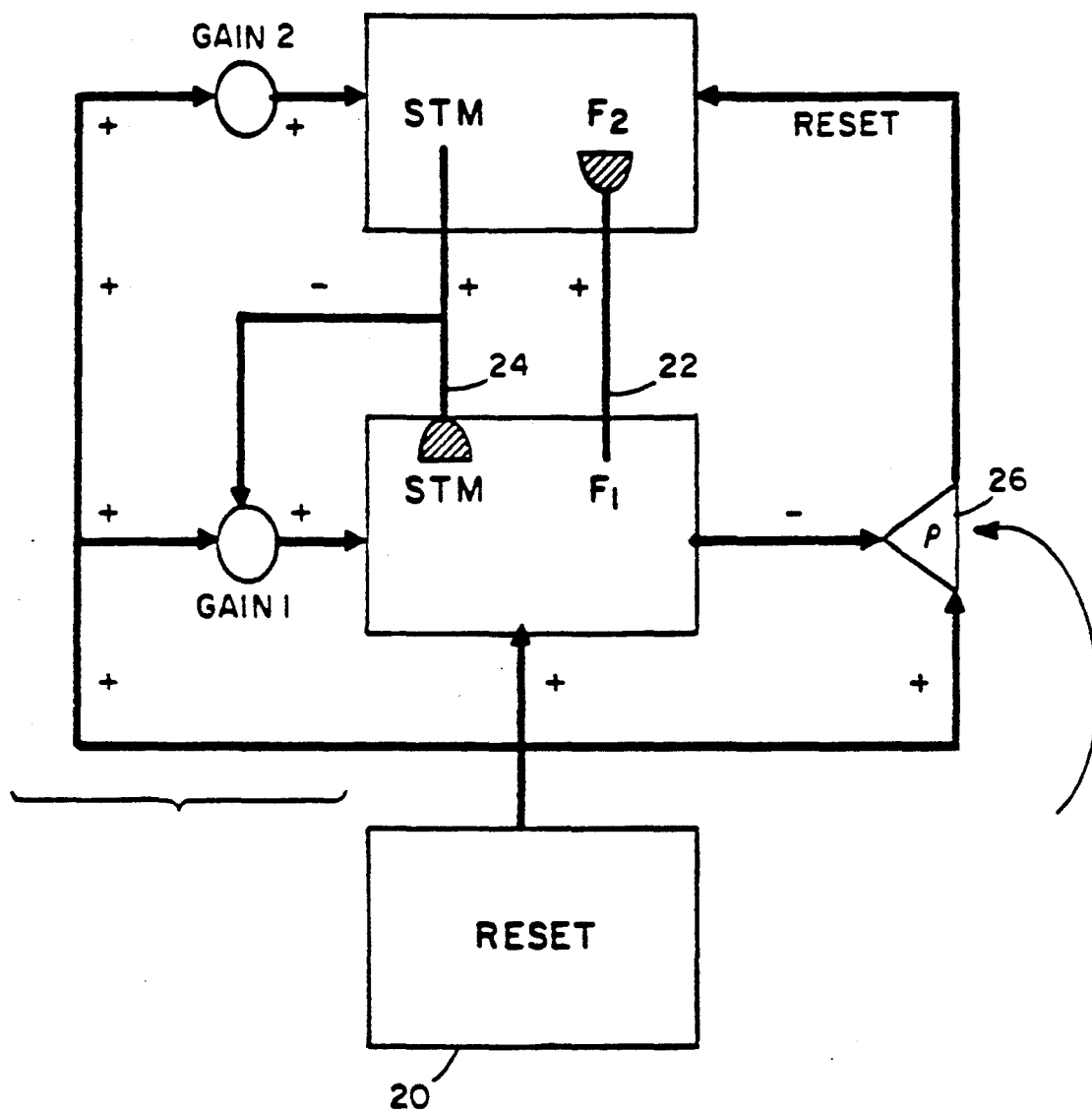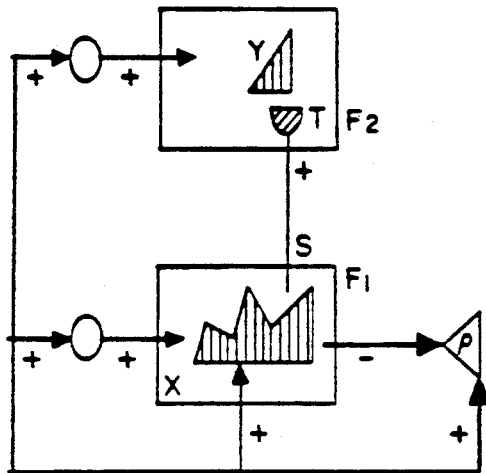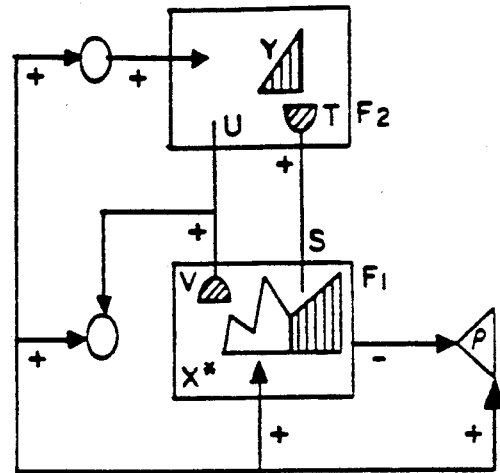
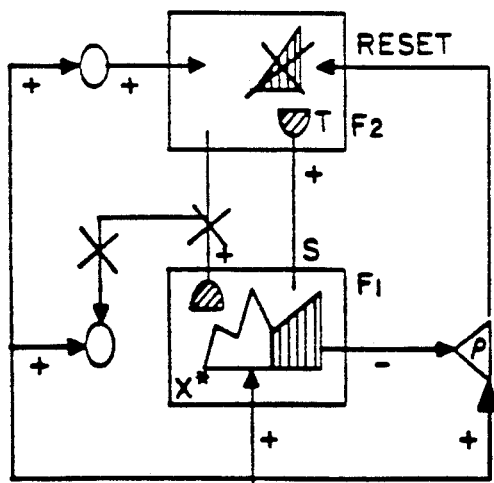26 Claims, 21 Drawing Sheets

FIG. 1 (PRIOR ART)

FIG. 2a

FIG. 2b

FIG. 2c
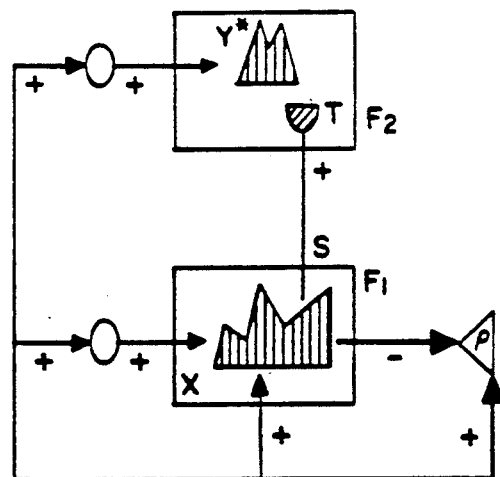
FIG. 2d
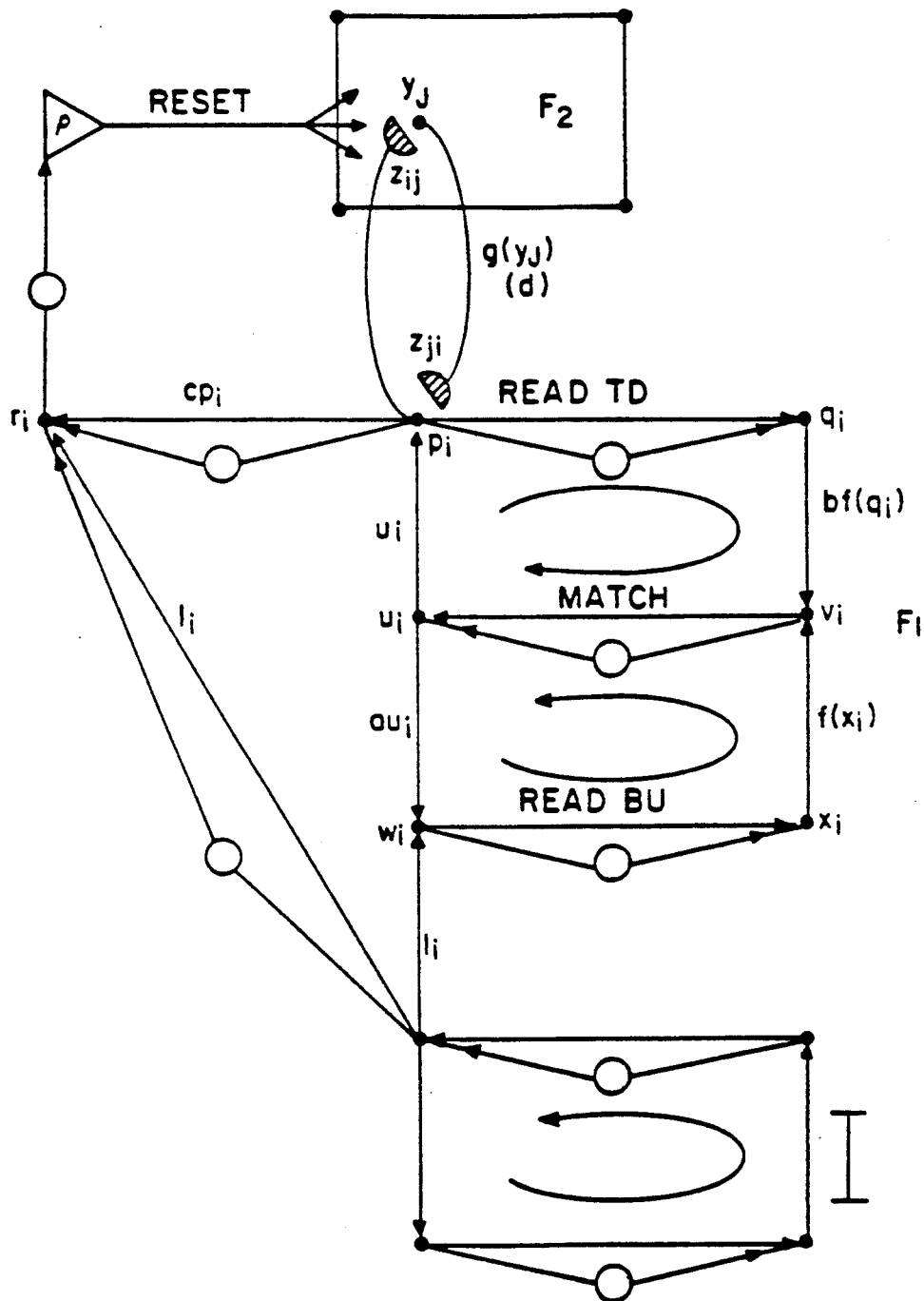
FIG. 3 (PRIOR ART)

FIG. 4

ART CASCADE

MODULE C

RESET B

P_B

F_{2B}

MODULE B

F_{1B}

F_{2A}

RESET A

P_A

MODULE A

F_{1A}

INPUT

FIG. 5

NODE i ——→ NODE j

PATH WEIGHT
Z_{ij}

→ S_i
PRESYNAPTIC
SIGNAL

u_{ij}

PRESYNAPTIC
TRANSMITTER

→ v_{ij}

RELEASED
AND BOUND
TRANSMITTER

x_j
POSTSYNAPTIC
ACTIVATION

FIG. 6

LEARNING

O $t = 0^+$
$x_j \cong 0$

t

INPUT
ON

MISMATCH
RESETS

INPUT
OFF

INPUT
ON

x_i ——→ CONTRAST – ENHANCED
STEADY STATE

FIG. 7

FIG. 8

FIG. 9a

FIG. 9b

PARTIAL
COMPRESSION

FIG. 9c

CHOICE

FIG. 9d

FIG. 10

FIG. 11

$S \cdot u_j \cong$
$S \cdot z_j$

$t = 0^+$

↑
GOOD
PATTERN
MATCH

J
↑
LARGE
WEIGHTS
$|z_J|$

FIG. 12a

$\sum_i v_{ij}$

CHOICE,
RESET

FIG. 12b

AFTER RESET

$S \cdot u_j$

↑   J
↑

CHOOSE J AGAIN,
UNTIL ANOTHER
NODE CAN WIN

FIG. 12c

INPUT
ON

$I = 0$

CONTRAST
ENHANCEMENT

z_j AND $\sum_i v_{ij}$

MISMATCH
RESET

INACTIVATION
OF BOUND
TRANSMISSION

INPUT
OFF

INSET
RESET

$x_j \approx$

$S \cdot u_j \approx$

$S \cdot z_j$

$x_j \approx$

$S \cdot u_j \neq$

$S \cdot z_j$

t

FIG. 13
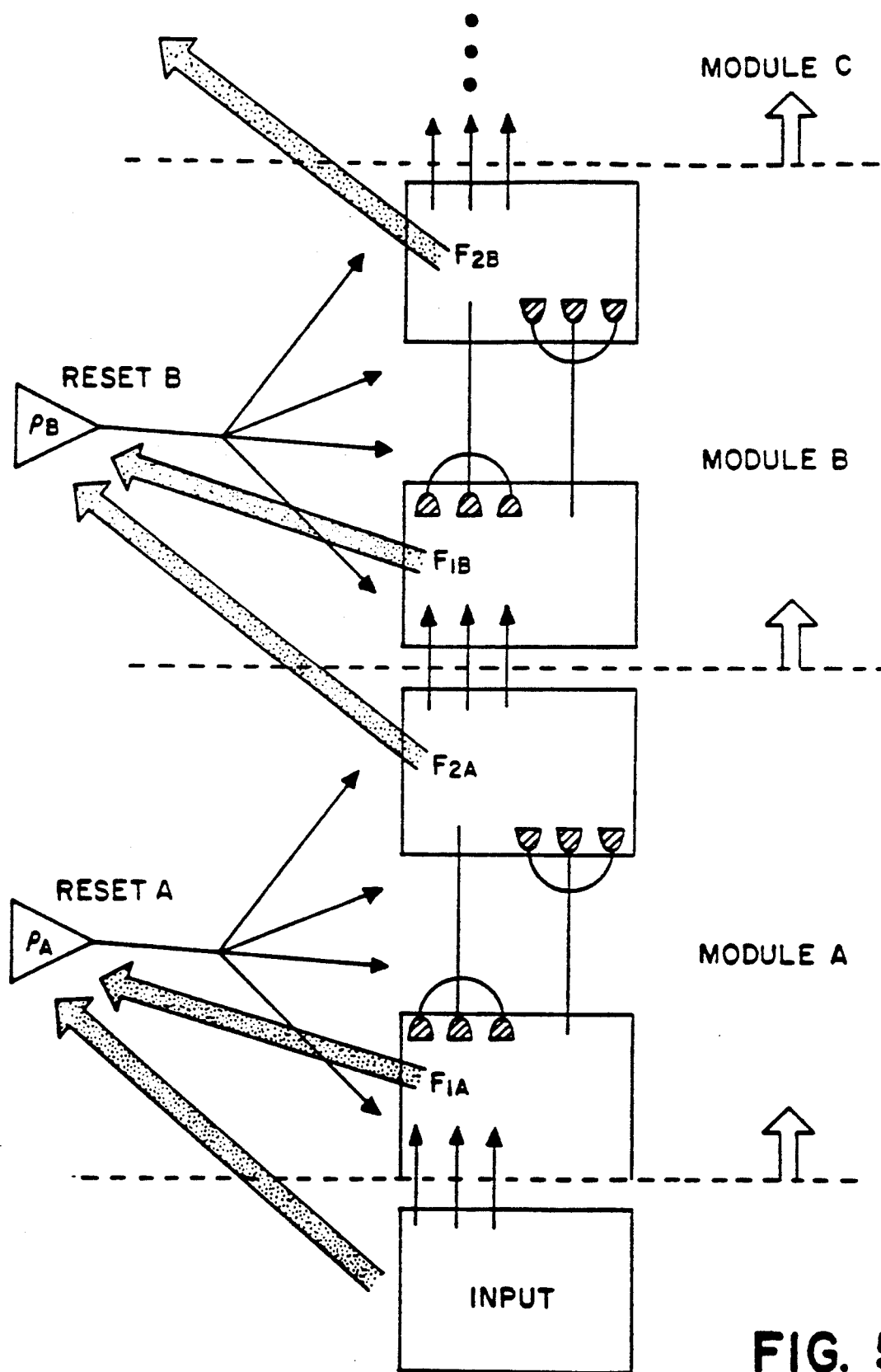
FIG. 14a

FIG. 14b

FIG. 15a

FIG. 15b

ART 3

RESET

SIGNAL FUNCTIONS
(L = 1, 2, 3)

$$S_i^{aL} = g^a(y_i^{aL})$$

$$S_i^{bL} = g^b(y_i^{bL})$$

$$S_i^{cL} = g^c(y_j^{cL})$$

FIG. 16

$$S^{b3} \equiv g^{b}(y_i^{b3}) \qquad\qquad\qquad z_{ij}^{bc}$$

INPUT i

$$S^{b3} \; z_j^{bc}$$

SCALE

$$\cos(S^{b3}, z^{bc})$$

FIG. 17a

$$S_i^{b3} \equiv q_i^b(y^{b3}) \qquad z_{ij}^{bc}$$

FIG. 17b

F_C STM

$y_j^{c\,1}$

INPUT 1

1.0

INPUT 2

1 2 3 4 5 6 7

$j \longrightarrow$

FIG. 18a

BOTTOM - UP

$\sum\limits_{i} v_{ij}^{bc}$

INPUT 1

1.0

INPUT 2

2 3 4 5 6 7

$j \longrightarrow$

FIG. 18b

TOP - DOWN

$\sum\limits_{i} v_{ji}^{c\,b}$

INPUT 1

INPUT 2

4 5 6 7

$i \longrightarrow$

FIG. 18c

F_C STM

$y_j^{c\,1}$

INPUT 1

INPUT 2

FIG. 19a

BOTTOM - UP

$\sum_i v_{ij}^{b\,c}$

INPUT 1

INPUT 2

FIG. 19b

TOP - DOWN

$\sum_j v_{ji}^{c\,b}$

INPUT 1

INPUT 2

FIG. 19c

F_c STM

$y_j^{c\ 1}$

INPUT 1

1.0

INPUT 2

$j \longrightarrow$

FIG. 20a

BOTTOM - UP

$\sum\limits_{i} v_{i\ j}^{b\ c}$

INPUT 1

1.0

INPUT 2

$j \longrightarrow$

FIG. 20b

TOP - DOWN

$\sum\limits_{j} v_{j\ i}^{c\ b}$

INPUT 1

1.0

INPUT

$i \longrightarrow$

FIG. 20c

F_C STM

$$y_j^{c\,1}$$

INPUT 1

INPUT 2

0.00

0.80

1.0

1.70

2.00

1 2 3 4 5 6 7

$j \longrightarrow$

FIG. 21a

BOTTOM - UP

$$\sum_i v_i^{b\,c}{}_j$$

INPUT 1

INPUT 2

0.00

0.80

1.0

1.70

2.00

1 2 3 4 5 6 7

$j \longrightarrow$

FIG. 21b

TOP - DOWN

$$\sum_j v^{c\,b}_{i\,j}$$

INPUT 1

INPUT 2

0.00

0.80

1.0

1.70

2.00

1 2 3 4 5 6 7

$i \longrightarrow$

FIG. 21c

F_C STM

$y_j^{c\ 1}$

INPUT 1

1.0

7.00

INPUT 2

9.00

1 2 3 4 5 6 7

$j \rightarrow$

FIG. 22a

BOTTOM-UP

$\sum_i v_{i\ j}^{b\ c}$

INPUT 1

1.0

7.00

INPUT 2

9.00

1 2 3 4 5 6 7

$j \rightarrow$

FIG. 22b

TOP-DOWN

$\sum_j v_{j\ i}^{c\ b}$

INPUT 1

1.0

7.00

INPUT 2

9.00

1 2 3 4 5 6 7

$i \rightarrow$

FIG. 22c

F_c STM

$y_j^{c\,1}$

INPUT 1

INPUT 2

1.0

0.00

0.80

1.00

1   2   3   4   5   6   7

$j \longrightarrow$

FIG. 23a

BOTTOM - UP

$\sum_i v_{i\,j}^{b\,c}$

INPUT 1

INPUT 2

1.0

0.00

0.80

1.00

1   2   3   4   5   6   7

$j \longrightarrow$

FIG. 23b

TOP - DOWN

$\sum_j v_{j\,1}^{c\,b}$

INPUT 1

INPUT 2

1.0

0.00

0.80

1.00

1   2   3   4   5   6   7

$i \longrightarrow$

FIG. 23c

HIERARCHICAL PATTERN RECOGNITION SYSTEM WITH VARIABLE SELECTION WEIGHTS

This application is a continuation-in-part (CIP) of application Ser. No. 07/464,247, filed Jan. 12, 1990, and now abandoned.

BACKGROUND OF THE INVENTION

Adaptive Resonance Theory (ART) architectures are neural networks that carry out stable self-organization of recognition codes for arbitrary sequences of input patterns. Adaptive Resonance Theory first emerged from an analysis of the instabilities inherent in feedforward adaptive coding structures (Grossberg, 1976a). More recent work has led to the development of two classes of ART neural network architectures, specified as systems of differential equations. The first class, ART 1, self-organizes recognition categories for arbitrary sequences of binary input patterns (Carpenter and Grossberg, 1987a and U.S. patent application Ser. No. 07/086,732, filed Jul. 23, 1987). A second class, ART 2, does the same for either binary or analog inputs (Carpenter and Grossberg, 1987b and U.S. Pat. No. 4,914,708).

Both ART 1 and ART 2 use a maximally compressed, or choice, pattern recognition code. Such a code is a limiting case of the partially compressed recognition codes that are typically used in explanations by ART of biological data (Grossberg, 1982a, 1987). Partially compressed recognition codes have been mathematically analysed in models for competitive learning, also called self-organizing feature maps, which are incorporated into ART models as part of their bottom-up dynamics (Grossberg 1976a, 1982a; Kohonen, 1984). Maximally compressed codes were used in ART 1 and ART 2 to enable a rigorous analysis to be made of how the bottom-up and top-down dynamics of ART systems can be joined together in a real-time self-organizing system capable of learning a stable pattern recognition code in response to an arbitrary sequence of input patterns. These results provide a computational foundation for designing ART systems capable of stably learning partially compressed recognition codes. The present invention contributes to such a design.

The main elements of a typical ART 1 module are illustrated in FIG. 1. F_1 and F_2 are fields of network nodes. An input is initially represented as a pattern of activity across the nodes of feature representation field F_1. The pattern of activity across category representation F_2 corresponds to the category representation. Because patterns of activity in both fields may persist after input offset (termination of the input) yet may also be quickly inhibited, these patterns are called short term memory, or STM, representations. The two fields, linked by bottom-up adaptive filter 22 and top-down adaptive filter 24, constitute the Attentional Subsystem. Because the connection weights defining the adaptive filters may be modified by inputs and may persist for very long times after input offset, these connection weights are called long term memory, or LTM, variables.

Each node of F_1 is coupled to each node of F_2 through a weighted connection in the adaptive filter 22. Those weights change with learning. Thus, selection of a category node in F_2 is determined by the nodes which are activated by an input pattern and the weights from those nodes to F_2. Each node of F_2 is in turn connected to each node of F_1 through weighted connections of the adaptive filter 24. Those weights are also learned. The learned weights define a template pattern from a selected category, and that pattern is received at the nodes of F_1 through the adaptive filter 24. Intersection of the input pattern from input 20 and the template through the adaptive filter 24 is activated as a matching pattern in F_1. The norm of the matching pattern is compared to the norm of the input pattern at 26. If the comparison exceeds a threshold vigilance parameter ρ, the system is allowed to resonate and the adaptive filters 22 and 24 adjust their weights in accordance with the matching pattern. On the other hand, if the comparison does not exceed the vigilance parameter threshold, F_2 is reset and a different category is selected. Prior to receiving the template pattern through the adaptive filter 24, a gain control gain 1 activates all nodes which receive the input pattern. This is an implementation of the ⅔ Rule. Similarly, gain 2 activates F_2. Offset of the input pattern triggers offset of gain 2 and causes rapid decay of short term memory at F_2. F_2 is thereby prepared to encode the next input pattern without bias.

FIG. 2 illustrates a typical ART search cycle. An input pattern I at 20 (FIG. 1) registers itself as a pattern X of activity across F_1 (FIG. 2a). The F_1 output signal vector S is then transmitted through the multiple converging and diverging weighted adaptive filter pathways 22 emanating from F_1, sending a net input signal vector T to F_2. The internal competitive dynamics of F_2 contrast-enhance T. The F_2 activity vector Y therefore registers a compressed representation of the filtered $F_1 \rightarrow F_2$ input and corresponds to a category representation for the input active at F_1. Vector Y generates a signal vector U that is sent top-down through the second adaptive filter 24, giving rise to a net top-down signal vector V to F_1 (FIG. 2b). F_1 now receives two input vectors, I and V. An ART system is designed to carry out a matching process whereby the original activity pattern X due to input pattern I may be modified by the template pattern V that is associated with the current activity category. If I and V are not sufficiently similar according to a matching criterion established by a dimensionless vigilance parameter ρ at 26, a reset signal quickly and enduringly shuts off the active category representation (FIG. 2c), allowing a new category to become active. Search ensues (FIG. 2d) until either an adequate match is made or a new category is established.

In earlier treatments (e.g., Carpenter and Grossberg, 1987a), we proposed that the enduring shut-off of erroneous category representations by a nonspecific reset signal could occur at F_2 if F_2 were organized as a gated dipole field, whose dynamics depend on depletable transmitter gates. Though the new search process does not use a gated dipole field, it does retain and extend the core idea that transmitter dynamics can enable a robust search process when appropriately embedded in an ART system.

FIG. 3 shows the principal elements of a typical ART 2 module. It shares many characteristics of the ART 1

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module, having both an input representation field F_1 and a category representation field F_2, as well as Attentional and Orienting Subsystems. FIG. 3 also illustrates one of the main differences between the examples of ART 1 and ART 2 modules so far explicitly developed; namely, the ART 2 examples all have three processing layers within the F_1 field. These three processing layers allow the ART 2 system to stably categorize sequences of analog input patterns that can, in general, by arbitrarily close to one another. Unlike in models such as back propagation, this category learning process is stable even in the fast learning situation, in which the LTM variables are allowed to go to equilibrium on each learning trial.

In FIG. 3, one F_1 layers w,x reads in the bottom-up input, one layer p,q reads in the top-down filtered input from F_2, and a middle layer v,u matches patterns from the top and bottom layers before sending a composite pattern back through the F_1 feedback loop. Each of the nodes i of F_1 in ART 1 is now replaced by a set of nodes w_i, x_i, v_i, u_i, p_i and q_i. Like sets of those nodes span F_1 for processing of elements of the incoming pattern from an input stage I. Each of the large circles of FIG. 3 represents the computation of the L_2-norm of all the signals of a particular subfield, such as all of the signals w_i across the F_1 field. Each of the smaller circles denotes a computation to generate each of the subfield signals. Both F_1 and F_2 are shunting competitive networks that contrast-enhance and normalize their activation patterns (Grossberg, 1982a).

SUMMARY OF THE INVENTION

A model of the chemical synapse is incorporated into a new Adaptive Resonance Theory neural network architecture called ART 3. ART 3 system dynamics model a simple, robust mechanism for parallel search of a learned pattern recognition code. This search mechanism was designed to implement the computational needs of ART systems embedded in network hierarchies, where there can, in general, be either fast or slow learning and distributed or compressed code representations. This search mechanism incorporates a code reset property that serves at least three distinct functions: to correct erroneous category choices, to learn from reinforcement feedback, and to respond to changing input patterns.

In accordance with the present invention, a pattern recognition system comprises a short term feature representation field of nodes which support signals derived from input signals defining an input pattern. At least one category node of a category representation field is selected based on a pattern from the short term feature representation field. A category selection may be reset with insufficient match between the selected category and the input pattern. In accordance with the present invention, a category is selected by generating activation signals at nodes of the category representation field which are a function of signals from nodes of the feature representation field weighted by selection weights. The selection weights are initially set by long term memory but are reduced in medium term memory in selecting a category after reset of a category selection. Thus, during a search process for a category which provides a sufficient match, those elements of an input pattern which initially result in the strongest activation signal in F_2 due to initial weights or input pattern strength have a corresponding high reduction in selection weight with each reset. With this medium term reduction in selec-

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tion weights, the system automatically searches other categories in F_2 without requiring any specific inhibition in F_2.

In accordance with a further feature of the invention, contrast enhancement is obtained by further weighting signals from the feature representation field by the feedback of activation signals of nodes to which they are applied.

Preferably, the pattern recognition system is an ART system in which a long term memory template is generated based on the selected category, and that template is matched against the input pattern. Both the initial selection weights set by long term memory and the long term memory template are adapted to the input signals where a match is obtained.

In accordance with a further aspect of the invention, the category representation field of an ART system comprises a plurality of subfields of nodes supporting short term signals and feedback of short term signals within the short term field. Thus, the F_2 category representation field is homologous with the ART 2 F_1 feature representation field can thus serve as an F_1 field in a higher level ART system. Each of the short term signals of at least one subfield is based on signals specific to a category and also on nonspecific signals generated from across the short term field.

BRIEF DESCRIPTION OF THE DRAWINGS

The foregoing and other objects, features and advantages of the invention will be apparent from the following more particular description of preferred embodiments of the invention, as illustrated in the accompanying drawings in which like reference characters refer to the same parts throughout the different views. The drawings are not necessarily to scale, emphasis instead being placed upon illustrating the principles of the invention.

FIG. 1 illustrates a prior adaptive resonance theory (ART) system.

FIGS. 2a through 2d illustrate a search cycle in the system of FIG. 1.

FIG. 3 illustrates a prior ART 2 system.

FIG. 4 illustrates stages ART systems in which a center field serves as fields in both the lower and upper systems.

FIG. 5 illustrates an ART cascade of two ART modules.

FIG. 6 illustrates the structure of the adaptive filter in accordance with the present invention.

FIG. 7 is a timing chart illustrating operation of the present invention.

FIG. 8 is an illustration of a function used in setting the transmitter release rate.

FIG. 9a illustrates two fields of a system embodying the present invention; FIG. 9b illustrates the initial activation signal x_{ji} and FIGS. 9c and 9d illustrate the activation signal after contrast enhancement with partial compression and choice, respectively.

FIG. 10 illustrates changes in the activation signal with time.

FIG. 11 illustrates the bias against pathways after reset.

FIGS. 12a, b and c further illustrate the bias against pathways after reset.

FIG. 13 is a timing chart illustrating operation of the present invention.

FIGS. 14a and 14b illustrate a search process with reinforcement reset overriding path weight bias.

FIGS. 15a and 15b illustrate a search in which reinforcement reset overrides input bias.

FIGS. 16 identifies the specific signals in a system embodying the present invention.

FIGS. 17a, 17b, 18a-c, 19a-c, 20a-c, 22a-c, and 23a-c illustrate the results of simulations performed using the present invention.

DESCRIPTION OF A PREFERRED EMBODIMENT

In applications, ART modules are often embedded in larger architectures that are hierarchically organized. An example of one such hierarchy, a self-organizing model of the perception and production of speech is presented in Cohen, Grossberg, and Stork, 1988. Several copies of an ART module are cascaded upward, with partially compressed codes at each level. Top-down ART filters both within the perception system and from the production system to the perception system serve to stabilize the evolving codes as they are learned. We will now consider how an ART 2 module can be adapted for use in such a hierarchy.

When an ART module is embedded in a network hierarchy, it is no longer possible to make up a sharp distinction between the characteristics of the input representation field F_1 and the category representation field F_2. For example, within the auditory perception system of Cohen et al., the partially compressed auditory code acts both as the category representation field for the invariant feature field, and as the input field for the compressed item code field. As illustrated in FIG. 4, a Field F_a selects a category pattern that is a partially compressed code in category representation field F_b. F_b must then in turn serve as a feature representation field in selecting a category pattern in F_c. In order for fields to serve both functions, the basic structures of all the network fields in a hierarchical ART system should be homologous, in so far as possible. This constraint is satisfied if all fields of the hierarchy are endowed with the F_1 structure of an ART 2 module (FIG. 3). Such a design is sufficient for the F_2 field as well as the F_1 field because the principal property required of a category representation field, namely that input patterns be contrast-enhanced and normalized, is a property of the three-layer F_1 structure. The system shown in FIG. 4 is called an ART bidirectional hierarchy, with each field homologous to all other fields and linked to contiguous fields by both bottom-up and top-down adaptive filters.

For the ART hierarchy shown in FIG. 4, activity changes at any level can ramify throughout all lower and higher levels. It is sometimes desirable to buffer activity patterns at lower levels against changes at higher levels. This can be accomplished by inserting only a bottom-up pathway between two-field ART modules without a top down pathway as between F_{2A} and F_{1B} in FIG. 5. FIG. 5 illustrates a sequence of modules A,B,C . . . forming an ART cascade on. The fields are designated F_1 and F_2 as before; they are further designated by the module A or B. Module A generates a RESET A from F_{1A} and from the input in accordance with a vigilance parameter ρ_a. The specific mechanism within F_{1A} and F_{2A} is the subject of the present invention as described below. Similarly, module B is reset in response to signals from F_{2A} and F_{1B} in accordance with a vigilance parameter ρ_b. The "category representation" field F_{2A} acts as the input field for the next field F_{1B}. As in an ART 2 module (FIG. 3), connections from the input field F_{2A} to the first field F_{1B} of the next mod-

ule are nonadaptive and unidirectional. Connections between F_{1B} and F_{2B} are adaptive and bidirectional. This scheme repeats itself throughout the hierarchy. Activity changes due to a reset event at a lower level can be felt at higher levels via an ascending cascade of reset events. In particularly, reset at the lower input level can lead to a cascade of input reset events up the entire hierarchy.

We now consider the problem of implementing parallel search among the distributed codes of a hierarchical ART system. Assume that a top-down/bottom-up mismatch has occurred somewhere in the system. How can a reset signal search the hierarchy in such a way that an appropriate new category is selected? The search scheme for ART 1 and ART 2 modules incorporates an asymmetry in the design of levels F_1 and F_2 that is inappropriate for ART hierarchies whose fields are homologous. The ART 3 search mechanism described below eliminates that asymmetry.

A key observation is that a reset signal can act upon an ART hierarchy between its field $F_a, F_b, F_c \ldots$. Locating the site of action of the reset signal between the fields allows each individual field to carry out its pattern processing function without introducing processing biases directly into a field's internal feedback loops.

The new ART search mechanism has a number of useful properties. It: (a) works well for mismatch, reinforcement, or input reset; (b) is simple; (c) is homologous to physiological processes; (d) fits naturally into network hierarchies with distributed codes and slow or fast learning; (e) is robust in that it does not require precise parameter choices, timing, or analysis of classes of inputs; (f) requires no new anatomy, such as new wiring or nodes, beyond what is already present in the ART 2 architecture; (g) brings new computational power to the ART systems; and (h) although derived from the ART system, can be used to search other neural network architectures as well.

The computational requirements of the ART search process can be fulfilled by formal properties of neurotransmitters, if these properties are appropriately embedded in the total architecture model. The present search model specifies rate equations for transmitter production, release and inactivation as discussed below. The main properties used are illustrated in a chemical model in Ito (1984). In particular, the ART 3 search equations incorporates the dynamics of production and release of a chemical transmitter substance; the inactivation of transmitter at postsynaptic binding sites; and the modulation of these processes via a nonspecific control signal. The net effect of these transmitter processes is to alter the ionic permeability at the postsynaptic membrane site, thus effecting excitation or inhibition of the postsynaptic cell.

The neurotransmitter model is implemented in an ART 3 system by modifying the bottom-up adaptive filter 22 and the manner in which it effects activation of nodes in F_2. To illustrate the correspondence to the neurotransmitter model, terms such as transmitter and synapse are used herein. However, the present invention is directed to the implementation of a model so the transmitters are actually electronically stored values as are the activation signals. The signals are processed in accordance with the equations and procedures discussed below.

The notation to describe these transmitter properties is summarized in FIG. 6, for a synapse between the ith presynaptic node and the jth postsynaptic node. The

presynaptic signal, or action potential, S_i is received from a node in F_1 and arrives at a synapse whose adaptive weight, or long term memory trace, is denoted Z_{ij}. The variable z_{ij} is identified with the maximum amount of available transmitter. When the transmitter at this synapse is fully accumulated, the amount of transmitter u_{ij} available for release is equal to z_{ij}. When a signal S_i arrives, transmitter is typically released. The variable v_{ij} denotes the amount of transmitter released into the extracellular space, a fraction of which is assumed to be bound at the postsynaptic cell surface and the remainder rendered ineffective in the extracellular space. Finally, x_j denotes the activity, or membrane potential, of the postsynaptic cell, the F_2 node.

EQUATIONS FOR TRANSMITTER PRODUCTION, RELEASE, AND INACTIVATION

The search mechanism works well if it possesses a few basic properties. These properties can be realized using one of several closely related sets of equations, with corresponding differences in biophysical interpretation. An illustrative system of equations is described below.

Equations (1)–(3) govern the dynamics of the variables z_{ij}, u_{ij}, v_{ij}, and x_j at the ij^{th} pathway and j^{th} node of an ART 3 system.

Changes in presynaptic transmitter u_{ij} are governed by

$$\frac{du_{ij}}{dt} = (z_{ij} - u_{ij}) - u_{ij}R_r \tag{1}$$

where R_r is a release rate factor which will be shown in equation (9) to be a function of the presynaptic signal S_i and the postsynaptic activation x_j.

Changes in bound transmitter v_{ij} are governed by

$$\frac{dv_{ij}}{dt} = -v_{ij} + u_{ij}R_r - v_{ij}R_i$$
$$= -v_{ij} + u_{ij}R_r - v_{ij}S_{RES} \tag{2}$$

where R_i is an inactivation rate factor and S_{RES} is a reset signal.

Changes in postsynaptic activation x_j are governed by

$$\epsilon\frac{dx_j}{dt} = -x_j + (A - x_j)[\text{excitatroy inputs}] -$$
$$(B + x_j)[\text{inhibitory inputs}]$$
$$= -x_j + (A - x_j)\left[\sum_i v_{ij} + \{\text{intrafield feedback}\}\right] -$$
$$(B + x_j)S_{RES} \tag{3}$$

The first term to the right of equation (1) says that presynaptic transmitter is produced and/or mobilized until the amount u_{ij} of transmitter available for release reaches the maximum level z_{ij}. The adaptive weight z_{ij} itself changes on the slower time scale of learning, but remains essentially constant on the time scale of a single reset event. By the final terms of equation (1) available presynaptic transmitter u_{ij}, a selection weight, is released at a rate that is specified below.

But for a fraction which is inactivated, the released presynaptic transmitter u_{ij} because postsynaptic bound transmitter under equation (2). For simplicity, we ig-

nore the fraction of released transmitter that is inactivated in the extracellular space before bonding. Equation (2) says only that the bound transmitter is inactivated by the reset signal. In the absence of inputs, the term $-v_{ij}$ indicates that the activity of v_{ij} passively decays to zero as the released and bound transmitters are dissipated.

Equation (3) for the postsynaptic activity x_j is a shunting mechanism equation such that excitatory inputs drive x_j up toward a maximum depolarized level equal to A; inhibitory inputs drive x_j down toward a minimum hyperpolarized level equal to $-B$; and activity passively decays to a resting level equal to 0 in the absence of inputs. The net effect of bound transmitter at all synapses converging on the jth node is assumed to be excitatory, via the term

$$\Sigma v_{ij}$$

Internal feedback from within the target field (FIG. 3) is excitatory, while the nonspecific reset signal is inhibitory. Parameter ϵ in equations (3) is small, corresponding to the assumption that activation dynamics are fast relative to the transmitter accumulation rate, equal to 1 in the first term to the right of equation (1).

The ART 3 system can be simplified for purpose of simulation. Suppose that $\epsilon << 1$ in (3); the reset signals in (2) and (3) are either 0 or $>> 1$; and net intrafield feedback is excitatory. Then equations (1), (5), and (6) below approximate the main properties of ART 3 system dynamics.

The simplified ART 3 Equations are then:

$$\frac{du_{ij}}{dt} = (z_{ij} - u_{ij}) - u_{ij}R_r \tag{1}$$

$$\begin{cases} \dfrac{dv_{ij}}{dt} = -v_{ij} + u_{ij}R_r & \text{if reset} = 0 \\ v_{ij}(t) = 0 & \text{if reset} >> 1 \end{cases} \tag{5}$$

$$x_j(t) = \begin{cases} \Sigma_i v_{ij} + [\text{intrafield feedback}] & \text{if reset} = 0 \\ 0 & \text{if reset} >> 1. \end{cases} \tag{6}$$

In equations (2) and (3), the reset signal acts in two ways, by inactivating bound transmitter and directly inhibiting the postsynaptic membrane. Alternatively, the reset signal may accomplish both these goals in a single process if all excitatory inputs in (3) are realized using chemical transmitters. Letting w_j denote the net excitatory transmitter reaching the jth target cell via intrafield feedback, an illustrative system of this type is given by equations (1), (2), (7) and (8) below.

Presynaptic Transmitter:

$$\frac{du_{ij}}{dt} = (z_{ij} - u_{ij}) - u_{ij}R_r \tag{1}$$

Bound Transmitter:

$$\frac{dv_{ij}}{dt} = -v_{ij} + u_{ij}R_r - v_{ij}S_{RES} \tag{2}$$

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-continued

$$\frac{dw_j}{dt} = -w_j + \text{[intrafield feedback]} - w_jS_{RES} \tag{7}$$

Postsynaptic Activation:

$$\epsilon \frac{dx_j}{dt} = -x_j + (A - x_j)\left(\sum_i v_{ij} + w_j\right) \tag{8}$$

The reset signal now acts as a chemical modulator that inactivates the membrane channels at which transmitter is bound. It thus appears in equations (2) and (7), but not in equation (8) for postsynaptic activation.

When the reset signal can be only 0 or $>>1$, the simplified system of equations (1), (5), and (6) approximates both versions of the ART 3 system. However, if the reset signal can vary continuously in size, equations (2), (7), and (8) can preserve relative transmitter quantities from all input sources. Thus this system is a better model for the intermediate cases than equations (2) and (3).

An additional inhibitory term in the postsynaptic activation equation (8) helps to suppress transmitter release, as illustrated in the simulation below.

TRANSMITTER RELEASE RATE

To further specify the ART search model, we now characterize the transmitter release and inactivation rates in equations (1) and (2). Then we trace the dynamics of the system at key time intervals during the presentation of a fixed input pattern (FIG. 7). We first observe system dynamics during a brief time interval after the input turns on ($t=0^+$), when the signal S_i first arrives at the synapse. We next consider the effect of subsequent internal feedback signals from within the target field, following contrast-enhancement of the inputs. We observe how the ART 3 model responds to a reset signal by implementing a rapid and enduring inhibition of erroneously selected pattern features. Then we analyse how the ART 3 model responds if the input pattern changes.

We will begin with the ART Search Hypothesis 1: Presynaptic transmitter u_{ij} is released at a rate jointly proportional to the presynaptic signal S_i and a function $f(x_j)$ of the postsynaptic activity. That is, in equations (1), (2), and (5), the release rate factor

$$R_r = S_if(x_j).$$

The function $f(x_j)$ in equation (9) has the qualitative properties illustrated in FIG. 8. In particular $f(x_j)$ is assumed to have a positive value when x_j is at its 0 resting level, so that transmitter u_{ij} can be released when the signal S_i arrives at the synapse. If $f(0)$ were equal to 0, no excitatory signal could reach a postsynaptic node at rest, even if a large presynaptic signal S_i were sent to that node. The function $f(x_j)$ is also assumed to equal 0 when x_j is significantly hyperpolarized, but to rise steeply when x_j is near 0. In the simulations, $f(x_j)$ is linear above a small negative threshold.

The form factor $S_if(x_j)$ is a familiar one in the neuroscience and neural network literatures. In particular, such a product is often used to model associative learning, where it links the rate of learning in the ijth pathway to the presynaptic signal S_i and the postsynaptic activity x_j. Associative learning occurs, however, on a time scale that is much slower than the time scale of

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transmitter release. On the fast time scale of transmitter release, the form factor $S_if(x_j)$ may be compared to interactions between voltages and ions in the chemical model. For example, note the dependence of the presynaptic signal on the Na^+ ion; the postsynaptic signal on the Ca^{2+} ion; and transmitter release on the joint fluxes of these two ions. The ART Search Hypothesis 1 thus formalizes a known type of synergetic relationship between presynaptic and postsynaptic processes in effecting transmitter release. Moreover, the rate of transmitter release is typically a function of the concentration of Ca^{2+} in the extracellular space, and this function has qualitative properties similar to the function $f(x_j)$ shown in FIG. 8 (Kandel and Schwartz, 1981, p. 84; Kuffler, Nichols, and Martin, 1984, p. 244).

SYSTEM DYNAMICS AT INPUT ONSET: AN APPROXIMATELY LINEAR FILTER

Some implications of the ART Search Hypothesis 1 will now be summarized. Assume that at time $t=0$ transmitter u_{ij} has accumulated at its maximal level z_{ij} and that activity x_j and bound transmitter v_{ij} equal 0. Consider a time interval $t=0^+$ immediately after a signal S_i arrives at the synapse. During this brief initial interval, the ART equations approximate the linear filter dynamics typical of many neural network models. In particular, equations (2) and (9) imply that the amount of bound transmitter is determined by equation

$$\frac{dv_{ij}}{dt} = -v_{ij} + u_{ij}S_if(x_j) - v_{ij}R_i \tag{10}$$

Thus at times $t=0^+$,

$$\frac{dv_{ij}}{dt} \approx z_{ij}S_if(0) \tag{11}$$

and so

$$v_{ij}(t) \approx K(t)S_iz_{ij} \text{ for times } t=0^+. \tag{12}$$

Because equation (12) holds at all the synapses adjacent to cell j, equation (6) implies that

$$x_j(t) \approx \sum_i K(t)S_iz_{ij} = K(t)S \cdot z_j \text{ for times } t = 0^+. \tag{13}$$

Here S denotes the vector $(s_1 \ldots s_n)$, z_j denotes the vector $(z_{1j} \ldots z_{nj})$, and $i=1 \ldots n$. Thus in the initial moments after a signal arrives at the synapse, the small amplitude activity x_j at the postsynaptic cell grows in proportion to the dot product of the incoming signal vector S times the adaptive weight vector z_j. FIG. 9a illustrates two fields, designated F_b and F_c to be consistent with FIG. 16, joined by a bottom-up filter 22 of weights z_{ij}. The initial short term memory activity x_j in F_c is illustrated in FIG. 9b.

SYSTEM DYNAMICS AFTER INTRAFIELD FEEDBACK

Amplification of Transmitter Release by Postsynaptic Potential

In the next time interval, the intrafield feedback signal contrast-enhances the Initial signal pattern (13) via equation (6) and amplifies the total activity across field F_c in FIG. 12. FIGS. 9c and 9d show typical contrast-

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enhanced activity profiles: partial compression of the initial signal pattern in FIG. 9c; or maximal compression, or choice, in FIG. 9d where only one postsynaptic node remains active due to the strong competition within the field F_c.

In all, the model behaves initially like a linear filter. The resulting pattern of activity across postsynaptic cells is contrast-enhanced, as required in the ART 2 model as well as in the many other neural network models that incorporate competitive learning (Grossberg, 1988). For many neural network systems, this combination of computational properties is all that is needed. These models implicitly assume that intracellular transmitter u_{ij} does not alter the rate of transmitter release:

$$u_{ij} \approx z_{ij} \text{ and } v_{ij} \approx z_{ij} S_i. \tag{14}$$

If the linear filtering properties implied by (14) work well for many purposes, why complicate the system by adding additional hypotheses? Even a new hypothesis that makes a neural network more realistic physiologically needs to be justified functionally, or it will obscure essential system dynamics. Why, then, add two additional nonlinearities to the portion of a neural network system responsible for transmitting signals from one location to another? The following discussion suggests how nonlinearities of synaptic transmission and neuromodulation can, when embedded in an ART circuit, help to correct coding errors by triggering a parallel search, allow the system to respond adaptively to reinforcement, and rapidly reset itself to changing input patterns.

In equation (10), term

$$u_{ij} S_i f(x_{ij}) \tag{15}$$

for the amount of transmitter released per unit time implies that the original incoming weighted signal $z_{ij} S_i$ is distorted both by depletion of the presynaptic transmitter u_{ij} and by the activity level x_j of the postsynaptic cell. If these two nonlinearities are significant, the net signal in the ijth pathway depends jointly on the maximal weighted signal $z_{ij} S_i$, the prior activity in the pathway, as reflected in the amount of depletion of the transmitter u_{ij}, and the immediate context in which the signal is sent, as reflected in the target cell activity x_j. In particular, once activity in a postsynaptic cell becomes large, this activity dominates the transmitter release rate, via the term $f(x_j)$ in (15). In other words, although linear filtering properties initially determine the small-amplitude activity pattern of the target field F_2, once intrafield feedback amplifies and contrast-enhances the postsynaptic activity x_j (FIGS. 9c and d), it plays a major role in determining the amount of released transmitter v_{ij} (FIG. 10). In particular, the postsynaptic activity pattern across the field F_c that represents the recognition code (FIG. 9d) is imparted to the pattern of released transmitter (FIG. 10), which then also represents the recognition code, rather than the initial filtered pattern $S \cdot z_j$.

SYSTEM DYNAMICS DURING RESET: INACTIVATION OF BOUND TRANSMITTER CHANNELS

The dynamics of transmitter release implied by the ART Search Hypothesis 1 can be used to implement the reset process, by postulating the

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ART Search Hypothesis 2: The nonspecific reset signal quickly inactivates postsynaptic membrane channels at which transmitter is bound.

The reset signal in equations (5) and (6) may be interpreted as assignment of a large value to the inactivation rate in a manner analogous to the action of a neuromodulator. Inhibition of postsynaptic nodes breaks the strong intrafield feedback loops that implement ART 2 and ART 3 matching and contrast-enhancement (equation (3) or (6)).

Let us now examine system dynamics following transmitter inactivation. The pattern of release transmitter can be viewed as a representation of the postsynaptic recognition code. The arrival of a reset signal implies that some part of the system has judged this code to be erroneous, according to some criterion. The ART Search Hypothesis 1 implies that the largest concentrations of bound extracellular transmitter are adjacent to the nodes which most actively represent this erroneous code. The ART Search Hypothesis 2 therefore implies that the reset process selectively removes transmitter from pathways leading to the erroneous representation.

After the reset wave has acted, the system is biased against activation of the same nodes, or features, in the next time interval: Whereas the transmitter signal pattern $S \cdot u_j$ originally sent to target nodes at times $t = 0^+$ was proportional to $S \cdot z_j$, as in equation (12), the transmitter signal pattern $S \cdot u_j$ after the reset event is no longer proportional to $S \cdot z_j$. Instead, it is selectively biased against those features that were previously active (FIG. 11). After a mismatch reset, the adaptive filter delivers a smaller signal $S \cdot u_j$ to the previously selected category representation, the one that generated the reset signal. This is because under equation 1 the presynaptic transmitters u_{ij} are drawn rapidly from the presynapse with R, being a function of $f(x_j)$ (equation 9), and the level of u_{ij} only rebuilds slowly with $(z_{ij} - u_{ij})$. The new signal pattern $S \cdot u_j$ will lead to selection of another contrast-enhanced representation, which may or may not then be reset. This search process continues until an acceptable match is found, possibly through the selection of a previously inactive representation.

Thus u_{ij} can be seen as a category selection weights which is initially set to equal the long term memory weight z_{ij} but which is reduced in category selection after reset. The amount of reduction of the selection weight is a function of the categories selected prior to reset. Because the change in selection weights continues after reset the selection weights are stored for a longer term than are short term memory activations; yet they are changed over a much shorter term relative to the long term memory weights z_{ij}. The selection weights u_{ij} are thus medium term memory values.

This search process is relatively easy to implement, requiring no new nodes or pathways beyond those already present in ART 2 modules. It is also robust, since it does not require tricky timing or calibration. How the process copes with a typical slow learning situation is illustrated in FIGS. 12a, 12b and 12c. With slow learning, an input can select and begin to train a new category, so that the adaptive weights correspond to a perfect pattern match during learning. However, the input may not be on long enough for the adaptive weights to become very large. That inputs may later activate a different category node whose weights are large but whose vector of adaptive weights forms a poorer match than the original, smaller weights.

FIG. 12a shows such a typical filtered signal pattern $S \cdot z_j$. During the initial processing interval ($t = 0^+$) the transmitted signal $S \cdot u_j$ and the postsynaptic activity x_j are proportional to $S \cdot z_j$. Suppose that weights z_{ij} in pathways leading to the Jth node are large, but that the vector pattern z_j is not an adequate match for the signal pattern S according to the vigilance criterion. Also suppose that dynamics in the target field F_c lead to a "choice" following competitive contrast-enhancement (FIG. 12b), and that the chosen node J represents a category. Large amounts of transmitter will thus be released from synapses adjacent to node J, but not from synapses adjacent to other nodes. The reset signal will then selectively inactivate transmitter at postsynaptic sites adjacent to the Jth node. Following such a reset wave, the new signal pattern $S \cdot u_j$ will be biased against the Jth node relative to the original signal pattern. However, it could happen that the time interval prior to the reset signal is so brief that only a small fraction of available transmitter is released. Then $S \cdot u_j$ could still be large relative to a "correct" $S \cdot u_j$ after reset occurs (FIG. 12c). If this were to occur, the Jth node would simply be chosen again, then reset again, leading to an accumulating bias against that choice in the next time interval. This process could continue until enough transmitter v_{ij} is inactivated to allow another node, with smaller weights z_{ij} but a better pattern match, to win the competition. Simulations of such a reset sequence are illustrated below.

FIG. 13 summarizes system dynamics of the ART search model during a single input presentation. Initially the transmitted signal pattern $S \cdot u_j$, as well as the postsynaptic activity x_j, are proportional to the weighted signal pattern $S \cdot z_j$ of the linear filter. The postsynaptic activity pattern is then contrast-enhanced, due to the internal competitive dynamics of the target field. The ART Search Hypothesis 1 implies that the transmitter release rate is greatly amplified in proportion to the level of postsynaptic activity. A subsequent reset signal selectively inactivates transmitter in those pathways that caused an error. Following the reset wave, the new Signal $S \cdot u_j$ is no longer proportional to $S \cdot z_j$ but is, rather, biased against the previously active representation. A series of reset events ensue, until an adequate match or a new category is found. Learning occurs on a time scale that is long relative to that of the search process.

AUTOMATIC STM RESET BY REAL-TIME INPUT SEQUENCES

The ART 3 architecture serves other functions as well as implementing the mismatch-reset-search cycle. In particular it allows an ART system to dispense with additional processes to reset STM with an onset or offset of an input pattern. The representation of input patterns as a sequence, $I_1, I_2, I_3, \ldots$, corresponds to the assumption that each input is constant for a fixed time interval. In practice, an input vector $I(t)$ may vary continuously through time. The input need never be constant over an interval, and there may be no temporal marker to signal offset or onset of "an input pattern" per se. Furthermore, feedback loops within a field or between two fields can maintain large amplitude activity even when $I(t) = 0$. Adaptive resonance develops only when activity patterns across fields are amplified by such feedback loops and remain stable for a sufficiently long time to enable adaptive weight changes to occur

(Grossberg, 1976b, 1982a). In particular, no reset waves are triggered during a resonant event.

The ART reset system functionally defines the onset of a "new" input as a time when the orienting subsystem emits a reset wave. This occurs, for example, in the ART 2 module (FIG. 3) when the angle between the vectors $I(t)$ and $p(t)$ becomes so large that the norm of $r(t)$ falls below the vigilance level $\rho(t)$, thereby triggering a search for a new category representation. This is called an input reset event, to distinguish it from a mismatch reset event, which occurs while the bottom-up input remains nearly constant over a time interval but mismatches the top-down expectation that it has elicited from level F_2 (FIG. 2).

This property obviates the need to mechanically define the processing of input onset or offset. The ART Search Hypothesis 3, which postulates restoration of a resting state between successive inputs (Carpenter and Grossberg, 1989), is thus not needed. Presynaptic transmitter may not be fully accumulated following an input reset event, just as it is not fully accumulated following a mismatch reset event. For both types of reset, the orienting subsystem judges the active code to be incorrect, at the present level of vigilance, and the system continues to search until it finds an acceptable representation.

REINFORCEMENT FEEDBACK

The mechanisms described thusfar for STM reset are part of the recognition learning circuit of ART 3. Recognition learning is, however, only one of several processes whereby an intelligent system can learn a correct solution to a problem. We have called Recognition, Reinforcement, and Recall the "3 R's" of neural network learning (Carpenter and Grossberg, 1988).

Reinforcement, notably reward and punishment, provides additional information in the form of environmental feedback based on the success of failure of actions triggered by a recognition event. Reward and punishment calibrate whether the action has or has not satisfied internal needs, which in the biological case include hunger, thirst, sex, and paid reduction, but may in machine applications include a wide variety of internal cost functions.

Reinforcement can shift attention to focus upon those recognition codes whose activation promises to satisfy internal needs based on past experience. A model to describe this aspect of reinforcement learning was described in Grossberg, (1982a, 1982b, 1984; reprinted in Grossberg, 1987a) and was supported by computer simulations in Grossberg and Levine (1987; reprinted in Grossberg, 1988). An attention shift due to reinforcement can also alter the structure and learning of recognition codes by amplifying (or suppressing) the STM activations, and hence the adjacent adaptive weights, of feature detectors that are active during positive (or negative) reinforcement.

A reset wave may also be used to modify the pattern of STM activation in response to reinforcement. For example, both green and yellow bananas may be recognized as part of a single recognition category until reinforcement signals, contingent upon eating the bananas, differentiate them into separate categories. Within ART 3, such a reinforcement signal can alter the course of recognition learning by causing a reset event. The reset event may override a bias in either the learned path weights (FIGS. 14a and b) or in the input strengths (FIGS. 14a and b) that could otherwise prevent a cor-

rect classification from being learned. FIGS. 14a and b illustrate a system whose weights are biased toward feature A over feature B over feature C. In FIG. 14a, competition amplifies the weight bias in STM, leading to enhanced transmitter release of the selected feature A. In FIG. 14b, transmitter inactivation following reinforcement reset allows feature B to become active in STM.

FIGS. 15a and b illustrate a system whose input signals are biased towards A over B over C. In FIG. 15a, competition amplifies the input bias in STM, leading to enhanced transmitter release of the selected feature A. In FIG. 15b, transmitter inactivation following reinforcement reset allows feature B to become active in STM.

For example, both green and yellow bananas may initially be coded in the same recognition category because features that code object shape (e.g., pathway A in FIGS. 14 and 15) prevent features that code object color (e.g., pathway B in FIGS. 14 and 15) from being processed in STM activities of these shape features until both shape and color features can simultaneously be processed, and thereby incorporated into different recognition codes for green bananas and yellow bananas.

In technological applications, such a reset wave can be implemented as a direct signal from an internal representation of a punishing event. The effect of the reset wave is to modify the spatial pattern of STM activation whose read-out into an overt action led to the punishing event. The adaptive weights, or LTM traces, that input to these STM activations are then indirectly altered by an amount that reflects the new STM activation pattern. Such a reinforcement scheme differs from the competitive learning scheme described by Kohonen (1984, p. 200), in which reinforcement acts directly, and by an equal amount, on all adaptive weights that lead to an incorrect classification.

Reinforcement may also act by changing the level of vigilance (Carpenter and Grossberg, 1987a, 1987b). For example, if a punishing event increases the vigilance parameter, then mismatches that were tolerated before will lead to a search for another recognition code. Such a code can help to distinguish pattern differences that were previously considered too small to be significant. Such a role for reinforcement is illustrated by computer simulations below.

All three types of reaction to reinforcement feedback may be useful in applications. The change in vigilance alters the overall sensitivity of the system to pattern differences. The shift in attention and the reset of active features can help to overcome prior coding biases that may be maladaptive in novel contexts.

TABLE 1

NOTATION FOR ART 3 HIERARCHY

$F_{field} = F_a$	STM field a
$i = i_a = 1 \ldots n_a$	node index, field a
$L = 1,2,3$	index, 3 layers of an STM field
x_i^{aL}	STM activity, input node i, layer L, field a
y_i^{aL}	STM activity, output node i, layer L field a
$g^a(y_i^{aL}) = S_i^{aL}$	signal function, field a
p_k^a	parameter, field a, $k = 1, 2, \ldots$
r_i^b	STM activity, reset node i. field b
p^b	vigilance parameter, field b
z_{ij}^{bc}	LTM trace, pathway from node i (field b) to node j (field c)
u_{ij}^{bc}	intracellular transmitter, pathway from node i (field b) to node j (field c)
v_{ij}^{bc}	released transmitter, pathway from

TABLE 1-continued

NOTATION FOR ART 3 HIERARCHY

node i (field b) to node j (field c)

NOTATION FOR HIERARCHIES

Table 1 and FIG. 16 illustrate notation suitable for an ART hierarchy with any number of fields $F_a, F_b, F_c \ldots$ This notation can also be adapted for related neural networks and algorithmic computer simulation.

Each STM variable is indexed by its field, layer, and node number. Within a layer, x denotes the activity of a node receiving inputs from other layers, while y denotes the (normalized) activity of a node that sends signals to other layers. For example, x_i^{a2} denotes activity at the ith input node in layer 2 of field F_a (i = 1 ... n_a); and y_i^{a2} denotes activity of the corresponding output node. Parameters are also indexed by field ($p_1^a, p_2^a, \ldots$), as are signal functions (g^a). Variable r_i^b denotes activity of the ith reset node of field F_b, and p^b is the corresponding vigilance parameter.

Variable z denotes an adaptive weight or LTM trace. For example, z_{ij}^{bc} is the weight in the bottom-up pathway from the ith node of field F_b to the jth node of field F_c. Variable u_{ij}^{bc} and v_{ij}^{bc} denote the corresponding presynaptic and bound transmitter quantities, respectively. Variables for the top-down pathways are z_{ji}^{cb}, u_{ji}^{cb} and v_{ji}^{cb}. Complete simulation equations are specified below.

SIMULATIONS

The simulations in FIGS. 17-23 illustrate the dynamics of search in the ART 3 system shown in FIG. 16. The simulation time scale is assumed to be short relative to the time scale of learning, so all adaptive weights z_{ij}^{bc} and z_{ij}^{bc} are held constant. The weights are chosen, however, to illustrate a problem that can arise with slow learning or in any other situation in which weight vectors are not normalized at all times. Namely, a category whose weight vector only partially matches the input vector may become active because its weights are large. This can prevent initial selection of another category whose weight vector matches the input vector but whose weight magnitudes are small due, say, to a brief prior learning interval.

The search process allows the ART 3 system to reject an initial selection with large weights and partial pattern match, and then to activate a category with small weights and a better pattern match. As in ART 2, when weights are very small (nodes j=6,7, ..., FIG. 21) the ART system tolerates poor pattern matches in order to allow new categories to become established. During learning with resonance, the weights can become larger. The larger the weights, the more sensitive the ART system is to pattern mismatch (Carpenter and Grossberg, 1987b).

FIG. 17 illustrates the trade-off between weight size and pattern match in the system used in the simulations. The length of a side of the square centered at position i or j or (i,j) gives the value of a variable with the corresponding index. Shown are quantities $S_i^{b3}, z_{ij}^{bc}, S^{b3}$, and cos ($S^{b3}, z_{ij}^{bc}$). In FIG. 17a Vector S^{b3} is the signal response to Input 1 in the simulations. Vector z_{ij}^{bc} (filled squares) is parallel to S^{b3}, but $||z_{ij}^{bc}||$ is small. Thus $S^{bc} \cdot z_{ij}^{bc}$ is smaller than $S^{b3} \cdot z_{ij}^{bc}$ or j= 1, 2, and 4, despite the fact that the cos (S^{b3}, z_{ij}^{bc}) is maximal. In FIG. 17b

Vector S^{b3} is the signal response to Input 2 in the simulations. Vector z_1^{bc} (filled squares) is parallel to S^{b3}. In FIGS. 17a and 17b, vector S illustrates the STM pattern stored in F_a and sent from F_a to F_b when an input vector I is held constant. The S_i values were obtained by presenting to F_a an input function I with I_i a linearly decreasing function of i. Vector S is also stored in F_b, as long as F_c remains inactive. Initially S is the signal vector in the bottom-up pathways from F_b to F_c. In FIG. 17a, $S_1 > S_2 > \ldots > S_5$; for i = 6,7 ... 15(=n_a=n_b), S_i is small. Each vector z_1, z_2, z_3, and z_4, plotted in columns within the square region of FIG. 17a, partially matches the signal vector S. These weights are significantly larger than the weights of vector z_5. However z_5 is a perfect match to S in the sense that the angle between the two vectors is 0:

$$\cos(S, z_5) = 1. \tag{16}$$

The relationship

$$S \cdot z_j = ||S|| \, ||z_j|| \cos(S, z_j). \tag{17}$$

implies a trade-off between weight size, as measured by the length $||z_j||$ of z_j, and pattern match, as measured by the angle between S and z_j. If the initial signal from F_b to F_c is proportional to $S \cdot z_j$, as in (13), then the matched mode (j = 5) may receive a net signal that is smaller than signals to other nodes. In fact, in FIG. 17a,

$$S \cdot z_1 > S \cdot z_2 > S \cdot z_4 > S \cdot z_5 > \ldots \tag{18}$$

FIG. 17b shows a signal vector S that is parallel to the weight vector z_1.

The computer simulations summarized in FIGS. 18–21 use the inputs described in FIG. 17 to illustrate the search process in an ART 3 system. In these simulations, the F_c competition parameters were chosen to make a choice; hence, only the node receiving the largest filtered input from F_b is stored in STM. The signal function of F_c caused the STM field to make a choice. In FIG. 22 a different signal function at F_c, similar to the one used in F_a and F_b, illustrates how the search process reorganizes a distributed recognition code. The simulations show how, with high vigilance, the ART search process rapidly causes a series of mismatch resets that alter the transmitter vectors $u_1, u_2, \ldots$ until $S \cdot u_5$ becomes maximal. Once node j = 5 becomes active in STM it amplifies transmitter release. Since the pattern match is perfect, no further reset occurs while Input 1 (FIG. 17a) remains on. Input reset is illustrated following an abrupt or gradual switch to Input 2 (FIG. 17b).

Each simulation figure illustrates three system variables as they evolve through time. The time axis (t) runs from the top to the bottom of the square. A vector pattern, indexed by i or j, is plotted horizontally at each fixed time. Within each square, the value of a variable at each time is represented by the length of a side of a square centered at that point. In each figure, part (a) plots y_j^c, the normalized STM variables at layer 1 of field F_c. Part (c) plots $\Sigma_i v_{ij}^{bc}$, the total amount of transmitter released, bottom-up, in paths from all F_b nodes to the jth F_c nodes to the ith F_b node. The ART Search Hypothesis 1 implies that the net bottom-up transmitter pattern in part (b) reflects the STM pattern of F_c in part (a); and that the net top-down transmitter pattern in part (c) reflects the STM pattern of F_b.

In FIG. 18, the vigilance parameter is high and fixed at the value

$$\rho = 0.98. \tag{19}$$

For $0 \leq t < 0.8$, the input (FIG. 17a) is constant. The high vigilance level induces a sequence of mismatch resets, alternating among the category nodes j = 1,2, and 4 (FIG. 18a), each of which receives an initial input larger than the input to node j = 5 (FIG. 17a). At t = 0.125, the F_c node j = 5 is selected by the search process (FIG. 18a). It remains active until t = 0.8. then, the input from F_a and the old reverberating STM pattern at F_b leads to an input reset (FIGS. 13 and 18). The ART Search Hypothesis 2 implies that bound transmitter is inactivated and the STM feedback loops in F_b and F_c are thereby inhibited. The new input pattern immediately activates its category node j = 1, despite some previous depletion at that node (FIG. 18a).

Large quantities of transmitter are released and bound only after STM resonance is established. In FIG. 18b, large quantities of bottom-up transmitter are released at the F_c node j = 5 in the time interval $0.215 < t < 0.8$, and at node j = 1 in the time interval $0.8 < t < 1$. In FIG. 18c, the pattern of top-down bound transmitter reflects the resonating matched STM pattern at F_b due to Input 1 at times $0.215 < t < 0.8$ and due to Input 2 at times $0.8 < t < 1$.

FIG. 19 shows the dynamics of the same system as in FIG. 19 but at the lower vigilance value

$$\rho = 0.94. \tag{20}$$

The F_c node j = 5 becomes active slightly sooner (t = 0.19, FIG. 17a) then it does in FIG. 19a, where $\rho = 0.98$. At a lower vigilance, more transmitter needs to be released before the system reacts to a mismatch so that each "erroneous" category node is active for a longer time interval than at higher vigilance. When $\rho = 0.98$ (FIG. 18b), node j = 1 is searched 5 times. When $\rho = 0.94$ (FIG. 19b), node j = 1 is searched only 3 times, but more transmitter is released during each activation/reset cycle than at comparable points in FIG. 18b. Inactivation of this extra released transmitter approximately balances the longer times to reset. hence the total search time remains approximately constant over a wide range of vigilance parameters. In the present instance, the nonlinearities of transmitter release terminate the search slightly sooner at lower vigilance.

FIG. 19a illustrates another effect of lower vigilance: the system's ability to tolerate larger mismatches without causing a reset. When the input changes at t = 0.8, the mismatch between the input pattern at F_a and the resonating pattern at F_b is not great enough to cause an input reset. Despite bottom-up input only to nodes i = 1,2, the strong resonating pattern at nodes i = 1 ... 4 maintains itself in STM at F_b (FIG. 19c).

In FIG. 26 vigilance is initially set at value

$$\rho = 0.9, \tag{21}$$

in the time interval $0 < t < 0.1$. At this low vigilance level, the STM pattern of F_b does not experience a mismatch reset series. Node j = 1 is chosen and resonance immediately ensure (FIG. 20a), as is also reflected in the amplification of transmitter release (FIG. 20b). The simulation illustrates a case where this choice of category leads to external consequences, including

reinforcement (Section 17), that feed back to the ART 3 moduel. This reinforcement teaching signal is assumed to cause vigilance to increase to the value

$$\rho = 0.98 \tag{22}$$

for times $t \geq 0.1$. This change triggers a search that ends at node $j = 5$, at time $t = 0.19$. Note that, as in FIG. 19, enhanced depletion of transmitter at $j = 1$ shortens the total search time. In FIG. 22, where ρ also equals 0.98, the search interval has length 0.215; in FIG. 20, the search interval has length 0.09, and the system never again activates node $j = 1$ during search.

The simulation illustrated in FIG. 21 is nearly the same as in FIG. 20, with $\rho = 0.9$ for $0 \leq t < 0.1$ and $\rho = 0.98$ for $t > 0.1$. However, at $t = 0.8$, Input 1 starts to be slowly deformed into Input 2, rather than being suddenly switched, as in FIG. 24. The $F_a \rightarrow F_b$ input vector becomes a convex combination of Input 1 and Input 2 that that starts as Input 1 ($t \leq 0.8$) and is linearly shifted to Input 2 ($t \geq 1.7$). Despite the gradually shifting input, node $j = 5$ remains active until $t = 1.28$. Then an input reset immediately leads to activation of node $j = 1$, whose weight vector matches Input 2. Competition in the category representation field F_c causes a history-dependent choice of one category or the other, not a convex combination of the two.

Issues of learning and code interpretation are subtle and complex when a code is distributed. However, the ART 3 search mechanism translates immediately into this context. The simulation in FIG. 22 illustrates how search operates on a distributed code. The only difference between the ART 3 system used for these simulations and the one used for FIGS. 18-21 is in the signal function at F_c. In FIGS. 18-21, a choice is always made at field F_c. The signal function for FIG. 21 is, like that at F_a and F_b, piecewise linear: 0 below a threshold, linear above. With its fairly high threshold, this signal function compresses the input pattern; but the compression is not so extreme as to lead inevitably to choice in STM.

Distributed code STM activity is shown in FIG. 22a. At a given time more than one active node may represent a category ($2.6 < t < 7$), or one node may be chosen ($7.7 < t \leq 9$).

ART 3 system satisfy the small number of design constraints described above. In addition ART 3 satisfies the ART 2 stability constraints (Carpenter and Grossberg, 1987b). For example, top-down signals need to be an order of magnitude larger than bottom-up signals, all other things being equal, as illustrated below by equation (24) and parameters p_1 and p_2 in Table 4 and equations (31) and (34). At least some of the STM fields need to be competitive networks. However, many versions of the ART systems exist within these boundaries. A simulation of one such system is illustrated in FIG. 23-27, which duplicates the conditions on ρ and input patterns of FIG. 21. However, the system that generated in FIG. 23 uses a different version of the ART 3 STM field F_c than the one described in the simulation equations section below. In particular, in the STM equation (3), $B > 0$. STM nodes can thus be hyperpolarized, so that $x_j < 0$, by intrafield inhibitory inputs. The transmitter release function $f(x_j)$ (equation (9)) equals 0 when x_j is sufficiently hyperpolarized. The system of FIG. 23 thus has the property that transmitter release can be terminated at nodes that become inactive during the STM competition. Since $f(0)$ needs to be positive in order to allow transmitter release to begin, low-level

transmitter release by nodes without significant STM activity is unavoidable if nodes cannot be hyperpolarized. FIG. 23 shows that a competitive STM field with hyperpolarization gives search and resonance results similar to those of the other simulations.

Similarly, considerable variations in parameters also give similar results.

SIMULATION EQUATIONS

Simulation equations are described in an algorithmic form to indicate the steps followed in the computer program that generated FIGS. 18-22.

The simulation time scale is fixed by setting the rate of transmitter accumulation equal to 1. The intrafield STM rate is assumed to be significantly faster, and the LTM rate significantly slower. Accordingly, STM equations are iterated several times each time step; and LTM weights are held constant. The simulation time step is

$$\Delta t = 0.005. \tag{23}$$

Transmitter variables u and v are integrated by first order approximation (Euler's method). The IMSL Gear package gives essentially identical solutions but requires more computer time.

The bottom-up LTM weights z_{ij}^{bc} illustrate in FIG. 22 are specified in Table 2. At "uncommitted" nodes ($j \geq 6$) $z_{ij}^{bc} = 0.001$. Top-down LTM weights z_{ij}^{cb} are constant multiples of corresponding z_{ij}^{bc} weights:

$$z_{ij}^{cb} = 10 \cdot z_{ij}^{bc} \tag{24}$$

TABLE 2

LTM WEIGHTS z_{ij}^{bc}

		$i \rightarrow$					
1	2	3	4	5	6		
1.0	0.0	0.0	1.0	0.176	0.0001	1	i
1.0	0.0	0.0	0.0	0.162	0.0001	2	j
0.0	0.9	0.0	0.0	0.148	0.0001	3	j
0.0	0.9	0.0	0.0	0.134	0.0001	4	j
0.0	0.0	0.8	0.0	0.120	0.0001	5	j
0.0	0.0	0.8	0.0	0.0	0.0001	6	j
0.0	0.0	0.0	0.0	0.0	0.0001	7	j
·	·	·	·	·	·		
·	·	·	·	·	·		
·	·	·	·	·	·		

$i = 1 \ldots n_a = n_b = 15$
$j = 1 \ldots n_c = 20$

This choice of LTM weights approximates a typical state of an ART system undergoing slow learning. Weights do not necessarily reach equilibrium on each presentation, but while the $J^{th}F_c$ node is active,

$$z_{ij}^{cb} \rightarrow x_i^{b3} \tag{25}$$

and

$$z_{ij}^{bc} \rightarrow S_i^{bc}. \tag{26}$$

Given the parameters specified below, as STM and LTM variables approach equilibrium,

$$x_i^{b3} = 10 \cdot S_i^{b3}. \tag{27}$$

Equations (25)-(27) imply that equation (24) is a good approximation of a typical weight distribution.

Initially,

$$u_{ij}^{bc}(0) = z_{ij}^{bc} \tag{28}$$

and

$$u_{ji}^{cb}(0) = z_{ji}^{cb}. \tag{29}$$

All other initial values are 0.

The F_b input values (S_i^{a3}) are specified in Table 3.

TABLE 3

	$F_a \to F_b$ INPUT VALUES (S_i^{a3})	
i	INPUT 1	INPUT 2
1	1.76	2.36
2	1.62	2.36
3	1.48	0.0
4	1.34	0.0
5	1.20	0.0
6	0.0	0.0
7	0.0	0.0
.	.	.
.	.	.
.	.	.

TABLE 4

PARAMETERS
$p_1^a = p_1^b = p_1^c = 10.0$
$p_2^a = p_2^b = p_2^c = 10.0$
$p_3^a = p_3^b = p_3^c = 0.0001$
$p_4^c = 0.9$
$p_5^b = p_5^c = 0.1$
$p_6^b = p_6^c = 1.0$

SIGNAL FUNCTIONS g^c, g^b, g^c		
F_a, F_b DISTRIBUTED	F_c CHOICE	F_c DISTRIBUTED
$p_7^a = p_7^b = 0.0$	$p_7^c = 1/\sqrt{n_c}$	$p_7^c = 0.0$
$p_8^a = p_8^{b\,l} = 0.3$	$p_8^c = 0.2$	$p_8^c = 0.4$
DISTRIBUTED		CHOICE

$$g(w) = \left\{ \begin{array}{ll} 0 & \text{if } w \leq p_7 + p_8 \\ \left(\dfrac{w - p_7}{p_8}\right) & \text{if } w > p_7 + p_8 \end{array} \right\} \qquad g(w) = \left\{ \begin{array}{ll} 0 & \text{if } w \leq p_7 \\ \left(\dfrac{w - p_7}{p_8}\right)^2 & \text{if } w > p_7 \end{array} \right\}$$

All simulations start with Input 1. Several of the simulations switch to Input 2 either with a jump or gradually. Input 1 values are obtained by presenting a linear, decreasing function I_i to F_a. Input 2 values are obtained by setting $I_1 = I_2 = 1$ and $I_i = 0 (i \geq 3)$.

Implicit in this formulation is the assumption that a changing input vector I can register itself at F_a. This requires that STM at F_a be frequently "reset." Otherwise new values of I_i may go unnoticed, due to strong feedback within F_a. Feedback within F_b allows the STM to maintain resonance even with fluctuating amplitudes at F_a.

Except during reset, equations used to generate the STM values for FIGS. 22–26 are similar to the ART 2 equations (Carpenter and Grossberg, 1987b). Dynamics of the fields F_a, F_b, and F_c are homologous, as shown in FIG. 26. Steady-state variables for the field F_b, when the reset signal equals 0, are given by equations (31)–(36). Similar equations hold for fields F_a and F_c.

Layer 1, input variable

$$\epsilon \frac{dx_i^{b1}}{dt} = -x_i^{b1} + S_i^{a3} + p_1^b S_i^{b2}. \tag{30}$$

-continued

In steady state,

$$x_i^{b1} = S_i^{a3} p_1^b S_i^{b2}. \tag{31}$$

Table 4 specifies parameter $p_1^b, p_2^b, \ldots$ values and the signal function

$$g^{bL}(y_i^{bL}) = g_i^{bL} \tag{32}$$

for layer $L = 1,2,3$. Equation (31) is similar to the simplified STM equation (6), with z_i^{b1} equal to the sum of an interfield input (g_i^{a3}) and an intrafield input (p_i^b, S_i^{b2}).

Layer 1, output variable

$$y_i^{b1} = \frac{x_i^{b1}}{p_3^b + \|x^{b1}\|} . \tag{33}$$

Layer 2, input variable

$$x_i^{b2} = S_i^{b1} + p_2^b S_i^{b3} \tag{34}$$

Layer 2, output variable

$$\tag{35}$$

$$y_i^{b2} = \frac{x_i^{b2}}{p_3^b + \|x^{b2}\|}$$

Layer 3, input variable

$$x_i^{b3} = S_i^{b2} + p_4^c \sum_j y_{ji}^{cb} \tag{36}$$

Layer 3, output variable

$$y_i^{b3} = \frac{x_i^{b2}}{p_3^b + \|x^{b2}\|} \tag{37}$$

Normalization of the output variables in equations (33), (35), and (37) accomplishes two goals. First, since the nonlinear signal function g^b in equation (32) has a fixed threshold, normalization is needed to achieve orderly pattern transformations under variable processing loads. This goal could have been reached with other norms, such as the L^1 norm $(\|x\| = \Sigma_i x_i)$. The second goal of normalization is to allow the patterns to have direct access to category representations, without search, after the code has stabilized (Carpenter and Grossberg, 1987a, 1987b). Equations (13) and (17) together tie the Euclidean norm to direct access in the present model. If direct access is not needed, or if an-

other measure of similarity of vectors is used, the Euclidean norm may be replaced by L^1 or another norm.

When the reset signal equals 0, levels of presynaptic and bound transmitter are governed by equations of the form (1) and (5), as follows.

Presynaptic transmitter, $F_b \rightarrow F_c$

$$\frac{du_{ij}^{bc}}{dt} = (z_{ij}^{bc} - u_{ij}^{bc}) - u_{ij}^{bc} p_5 b(x_j^{c1} + p_6 \gamma)S_i^{b3} \qquad (38)$$

Bound transmitter, $F_b \rightarrow F_c$

$$\frac{dv_{ij}^{bc}}{dt} = -v_{ij}^{bc} + u_{ij}^{bc} p_5 c(x_j^{c1} + p_6 \gamma)S_i^{b3} \qquad (39)$$

Presynaptic transmitter, $F_c \rightarrow F_b$

$$\frac{du_{ji}^{cb}}{dt} = (z_{ji}^{cb} - u_{ji}^{cb}) - u_{ji}^{cb} p_5 b(x_i^{b3} + p_6 b)S_j^{c1} \qquad (40)$$

Bound transmitter, $F_c \rightarrow F_b$

$$\frac{dv_{ji}^{cb}}{dt} = -v_{ji}^{cb} + u_{ji}^{cb} p_5 b(x_i^{b3} + p_6 b)S_j^{c1} \qquad (41)$$

Note that equations (38) and (39) imply that

$$u_{ij}^{bc} + v_{ij}^{bc} \rightarrow z_{ij}^{bc} \qquad (42)$$

and equations (40) and (41) imply that

$$u_{ji}^{cb} + v_{ji}^{cb} \rightarrow z_{ji}^{cb}. \qquad (43)$$

Reset occurs when patterns active at F_a and F_b fail to match according to the criterion set by the vigilance parameter. In FIG. 16,

$$r_i^b = \frac{y_i^{a2} + y_i^{b2}}{p_3^a + ||y^{a2}|| + ||y^{b2}||}. \qquad (44)$$

Reset occurs if

$$||r^b|| < p^b, \qquad (45)$$

where

$$0 < p^b < 1. \qquad (46)$$

As in equations (5) and (6), the effect of a large reset signal is approximated by setting input variables $x_i^{b1}, x^{b3}, x_j^{c1}, x_j^{c3}$ and bound transmitter variables v_{ij}^{bc}, v_{ji}^{cb} equal to 0.

ITERATION STEPS

Steps 1-7 outline the iteration scheme in the computer program used to generate the simulations.

Step 1. $t \rightarrow t + \Delta t$.

Step 2. Set p and S_i^{a3} values.

Step 3. Computer r_i^b and check for reset.

Step 4. Iterate STM equations F_b, F_c five times setting variables to 0 at reset.

Step 5. Iterate transmitter equations (38)-(41).

Step 6. Computer sums $\Sigma_i v_{ij}^{bc}$ and $\Sigma_j v_{ji}^{cb}$.

Step 7. Return to Step 1.

While this invention has been particularly shown and described with reference to a preferred embodiment thereof, it will be understood by those skilled in the art that various changes in form and details may be made therein without departing from the spirit and scope of the invention as defined by the appended claims.

We claim:

1. A pattern recognition data processing system comprising:
   a short term feature representation field of nodes supporting signals derived from input signals defining an input pattern;
   a category representation field of a plurality of nodes representing pattern categories;
   means for selecting at least one category node of the category representation field based on a pattern from the short term feature representation field; and
   means for resetting a category selection to cause continued search for an acceptable category selection;
   wherein the means for selecting generates activation signals at nodes of the category representation field which are a function of signals from nodes of the feature representation field weighted by selection weights, the selection weights being initially set for a category selection search by long term memory but being reduced when selecting at least one category after reset of a category selection.

2. A pattern recognition system as claimed in claim 1 wherein said selection weights are reduced as a function of the at least one category which is selected.

3. A pattern recognition system as claimed in claim 1 wherein, in generating the activation signals, the signals from nodes from the feature representation field are further weighted by corresponding activation signals to contrast enhance category selection.

4. A pattern recognition system as claimed in claim 1 further comprising means for adapting initial selection weights set by long term memory to the input pattern.

5. A pattern recognition system as claimed in claim 1 further comprising means for generating a long term memory template, based on the selected category, to be matched against the input pattern.

6. A pattern recognition system as claimed in claim 1 further comprising means for adapting the long term memory template to the input signals.

7. A pattern recognition system as claimed in claim 1 wherein the category representation field comprises a plurality of subfields of nodes supporting short term signals and feedback of short term signals within the short term field, each of the short term signals of at least one subfield being based on signals specific to a category and also on nonspecific signals generated from across the short term field.

8. A pattern recognition system as claimed in claim 1 further comprising a second category representation field and means for selecting at least one category of the second category representation field based on pattern from the first category representation field.

9. A method of pattern recognition in a pattern recognition data processing system comprising:
   storing input signals defining an input pattern in a short term feature representation field of nodes;
   selecting at least one category node of a category representation field comprised of a plurality of nodes representing pattern categories based on a pattern from the short term feature representation field; and
   resetting a category selection;
   in selecting at least one category node, generating activation signals at nodes of the category representation field which are a function of signals from nodes of the feature representation field weighted by selection weights, the method further compris-

ing initially setting the selection weights by long term memory and reducing the selection weights in selecting at least one category after reset of a category selection.

10. A method as claimed in claim 9 wherein the selection weights are reduced as a function of the at least one category which is selected.

11. A method as claimed in claim 9 further comprising, in generating the activation signals, weighting signals from nodes of the feature representation field by corresponding activation signals to contrast enhance category selection.

12. A method as claimed in claim 9 further comprising adapted initial selection weights set by long term memory to the input pattern.

13. A method as claimed in claim 9 further comprising generating a long term memory template, based on the selected category and matching the memory template against the input pattern to determine reset of a category selection.

14. A method as claimed in claim 9 further comprising adapting the long term memory template to the input signals.

15. A method as claimed in claim 9 further comprising, in the category representation field, supporting short term signals in a plurality of subfields and providing feedback of short term signals within the short term field, each of the short term signals of at least one subfield being based on signals specific to a category and also on nonspecific signals generated from across the short term field.

16. A method as claimed in claim 9 further comprising selecting at least one category of a second category representation field based on a pattern from the first category representation field.

17. A pattern recognition data processing system comprising:

a short term feature representation field of nodes supporting signals derived from input signals defining an input pattern and template signals defining a long term memory template;

means for selecting at least one category of a category representation field of nodes based on a pattern from the short term feature representation field;

means for generating the long term template based on ' the at least one selected category; and

means for adapting category selection and the long term memory template to the input signals;

the category representation field comprising a plurality of subfields of nodes supporting short term signals and feedback of short term signals within the category representation.

18. A pattern recognition system as claimed in claim 17 wherein at least one category is selected based on a pattern from the short term feature representation field weighted by selection weights, the system further comprising means for resetting a category selection, the selection weights being initially set by long term memory but being reduced, as a function of at least one

category which is selected, in selecting at least one category after reset of a category selection.

19. A pattern recognition system as claimed in claim 17 wherein, in generating the activation signals, the signal from nodes from the feature representation field are further weighted by corresponding activation signals to contrast enhance category selection.

20. A category selection system as claimed in claim 17 wherein each of the short term signals of at least one subfield is based on signals specific to a category and also on nonspecific signals generated from across the short term field.

21. A pattern recognition system as claimed in claim 17 further comprising a second category representation field, and means for selecting at least one category of the second category representation field based on a pattern from the first category representation field.

22. A method of pattern recognition in a pattern recognition data processing system comprising storing input signals in a short term representation field of nodes;

selecting at least one category of a category representation field comprised of a plurality of nodes representing pattern categories based on a pattern from the short term feature representation field;

generating a long term template based on the at least one selected category; and

adapting category selection and the long term memory template to the input signals;

the method further comprising, in the category representation field, generating short term signals in a plurality of subfields and providing feedback of short term signals within the category representation field.

23. A method as claimed in claim 22 further comprising selecting the at least one category based on a pattern from the short term feature representation field weighted by selection weights, and resetting the category selection with an insufficient match between the long term template and the input pattern in the feature representation field, the method further comprising initially setting the selection weights by long term memory but reducing the selection weights, as a function of at least one category which is selected, in selecting at least one category after reset of a category selection.

24. A method as claimed in claim 22 further comprising generating activation signals at nodes of the category representation field which are a function of signals from nodes of the feature representation field weighted by selection weights, the method further comprising further weighting signals from nodes from the feature representation field by corresponding activation signals to contrast enhance category selection.

25. A method as claimed in claim 22 wherein each of the short term signals of at least one subfield is based on signals specific to a category and also on nonspecific signals generated from across the short term field.

26. A method as claimed in claim 22 further comprising selecting at least one category of a second category representation field based on a pattern from the first category representation field.

* * * * *

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UNITED STATES PATENT AND TRADEMARK OFFICE
CERTIFICATE OF CO   CTION

PATENT NO. : 5,311,601

DATED   : May 10, 1994

INVENTOR(S) : Gail A. Carpenter and Stephen Grossberg

It is certified that error appears in the above-indentified patent and that said Letters Patent is hereby corrected as shown below:

In column 1, line 11, after "IRI-87-16960)," insert --and the Department of the Navy, Grant N00014-91-J-4100--.

Signed and Sealed this

Thirty-first Day of December, 1996

Attest:

BRUCE LEHMAN

Attesting Officer   Commissioner of Patents and Trademarks